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Optimizing Maintenance: Models with Applications to Marine Industry

No. 8B-1

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ABSTRACT

Past and current replacement models with applications to the marine industry for determining the optimum maintenance strategy are discussed. A new approach to multi-item replacement under budget constraints is presented. This approach considers all replacement decisions of an entire ship fleet. (or all component replacements of a single ship) simultaneously. A Lagrangian methodology for the replacement problem is also described.

LIST OF ACRONYMS

ARP Age Replacement Policy
IFR Increasing Failure Rate
MAM Multiplier Adjustment Method
MARP Modified Age Replacement Policy
MTTF Mean time To Failure
TTR Time To Repair

INTRODUCTION

With reduced manning levels and the ever increasing competition, ship maintenance has become one of the major problems in marine industry. Optimization of maintenance and replacement is very challenging due to highly restrictive and harsh operating conditions of ships. Moreover, these operating conditions, in many cases, are only known with a high level of uncertainty which makes the optimization problem even more complicated. However, lowering extremely high downtime costs by reducing emergency repairs caused by insufficient maintenance practices is always

desired. In the mean time, there is a delicate tradeoff between the cost of overmaintenance and the cost of avoided maintenance in keeping the shipping company competitive. Hence, the maintenance and replacement problem in the marine industry has conflicting multiple objectives, such as maximizing reliability and safety and minimizing costs simultaneously. As a result, optimization of marine maintenance becomes a very difficult and complicated problem (19,20).

Traditionally, many ship operators have been trying to solve maintenance optimization problem based on "experience" and "judgement" of managers basically using conservative manufacture's recommendations and rules of thumb (1,23). However using scientific techniques as opposed to ad hoc methods in maintenance optimization has been proved to be very rewarding in other industries (18). Naturally, there is a growing interest for just-in-time for maintenance and replacement management in the marine industry. During the last decade, artificial intelligence methods have been successfully applied to shipboard monitoring, container stowage planning (16,42), spare parts inventory management (34), and marine diesel engine fault diagnosis (29,30,35). In the mean time, the speed, storage capability and flexibility of computers have been tremendously improved during the last decade. At the same time, the use of computerized database systems for maintenance records has been growing. Hence, sophisticated maintenance models will increasingly become applicable as more data and computing capability are available.

In this paper, first past and current maintenance and replacement with applications in the marine industry are discussed. Then, a new approach to group replacement under budget constraints is presented. This approach considers all replacement decisions of an entire ship fleet (or all component replacements for a single ship) simultaneously. A Lagrangian methodology for the replacement problem is also presented.

MODELS

Marine maintenance and replacement optimization has conflicting multiple objectives. Simultaneous optimization of these objectives can be achieved by utilizing interactive techniques which involve the decision maker throughout the optimization process. A comprehensive list of papers (1965-1988) dealing with interactive multiple objective decision making is provided by Aksoy (2).

Maintenance and replacement models can be classified based on information availability, system type as single or multi-unit, time-event/action relationship, state-event/action relationship, model types, optimality criterion, solution methods, planning time horizon. Pierskalla and Voelker (43) surveyed maintenance models developed until 1976. Then, Sherif and Smith (45) classified deterministic and stochastic models in their 1981 survey. The authors used two distinct categories in their classification: preventive and preparedness models with and without complete information. Valdez-Florez and Feldman (48) presented models for single-unit systems. Very recently, Cho and Parlar (14) surveyed literature on optimal maintenance models for multi-unit systems.

We start this survey with a discussion of some basic characteristics of past and current optimal maintenance/replacement models based on planning time horizon, system state transition and maintenance criteria. We then briefly discuss individual replacement papers of potential interest to marine industry.

Basic Characteristics

Planning time horizon. Replacement problems may have a finite, infinite or random time horizon. Finite horizon problems occur when a system operates until a known termination time. For finite time horizon problems, the objective is finding the policy that will maximize the expected total revenue (or minimize expected total cost) generated by the system. One solution approach for the finite horizon problem is referred to as value iteration (27). The objective is to maximize average revenue per unit time (which is referred to as "gain") when no discounting is used, or to maximize the expected present value of future rewards in the case of discounting. To meet either objective, the policy iteration method is used (27).

System state transition. To model system state transition behavior, many existing replacement models assume a Markov process (4,17,24). Assuming exponential lifetimes (and hence constant hazard rates) for system components, these models ignore the effects of aging. However, the hazard rate of a mechanical component almost always varies with time. Hence the Markovian assumption is not very realistic for many mechanical components. To include the effects of break-in failures and/or aging, many authors (7,28) model the system behavior as a semi-Markov process (embedded Markov process).

Maintenance criteria. When a failure occurs, a decision maker usually has the "repair," "replace" and "do nothing" options. Many existing maintenance models assume that, when a failure occurs, it is best to replace the failed item, completely ignoring repair as another option (5,8,12,28,46), whereas some models also consider repair as another option (49,37). The time to repair and the time to replace are also considered in some models: While many models assume instantaneous repair and replacement times (10,36,33), others consider repair and replacement times as random variables.

There are many replacement policies, such as the Age Replacement Policy (ARP) (21,10,50,33), the Modified Age Replacement Policy (MARP) for intermittently used systems (36,7,8), replacement after N repairs (or N uses), and replacement based on failure risk.

Repairs are also classified as minimal and complete repairs. A minimal repair returns the failed item to its functioning condition just prior to failure, whereas complete repair brings the failed item to the "as good as new" condition (9,45). The degree of repair is also integrated into some models (33).

Selected Models

In the following, Some selected papers on system maintenance and replacement relevant to marine maintenance are discussed. The characteristics of models in terms of time horizon, system state transition and maintenance criteria are examined.

Kao (28) assumed that the system may be in one of i states ($i=0,1,2,\dots,L$), where state 0 corresponds to a "brand-new" System, state L corresponds to a failed system and others ($i = 1, 2, \dots, L - 1$) correspond to degraded (imperfect performance) states. He also assumed that there is only type Of replacement, and treated the system as one component. He proposed three replacement models, using the policy iteration method to minimize expected costs per unit time, under three rules; replacement based on system state, replacement based on system age and replacement based on both system state and age.

Mine et al. (36) considered optimal preventive replacement for intermittently used systems under two different criteria: 1) replacement after N USes, assuming time durations of uses to be random variables; and 2) replacement when Cumulative operating age reaches a specific time, T , before failure. Their objective was to find the values of N and T that minimize the mean cost rate over an infinite time horizon.

Berg (8) also studied preventive replacement policies for intermittently used units. He considered a modified age-replacement policy (MARP) under which the unit is replaced preventively When its age exceeds a critical Operational age. Provided that replacement times coincide with no-demand periods. Otherwise, preventive replacement is delayed until the end of the current demand period. His objective was to minimize the probability that the unit is down when it is demanded.

Thomas (47) developed a replacement model assuming that both the system (as a framework, like the body of a car) and its components (like tires, engine etc.) are independent of each other and can be replaced upon failure with many replacement alternatives. He ignored preventive maintenance completely. Repairs were not allowed.

WellS (49) examined a System over a finite random time horizon with non-zero repair and replacement times. To select whether to repair, replace or ignore a failed component, he introduced an optimal maintenance policy (which uses policy improvement and linear programming techniques). He assumed that a component will be repaired for its first N failures before ultimate replacement. He also assumed that duration of the System mission (life time etc.) is a random variable.

Most existing existing replacement models are restricted to single component models which can not be applied to multi-component Systems in an arbitrary setting, since some policies, as control limit policies, may not be optimal for multi-component systems. Most models developed for multi-component systems assume that the components are stochastically independent of each other, with increasing failure rate (IFR) lifetime distributions.

özekici (-10) studied the economic dependence between system components. He particularly focused on optimal replacement policies for functioning components in the presence of failed components. He discussed the stochastic and economic dependencies among system components, and formulated a

simple path analysis of the reliability system using Markov decision theory.

Boland and proschan (11,12). considered a system where replacements and overhauls were made at fixed multiples of some predetermined time, T . When a failure occurred, a minimal repair was performed. They calculated the period that minimized the total expected cost of repair and replacement cal-another period that minimized the total expected cost per unit time over an infinite time horizon.

Zuckerman (51) developed a maintenance strategy to optimize long-run average cost and total expected discounted cost over an infinite horizon. The system was subjected to shocks causing a random amount of damage to the system components. The system failed when failed when the accumulated damage exceeded a fixed threshold. For the optimal maintenance policy, the diffusion approximation model was Zuckermann showed that the optimal maintenance expenditure rate is monotonically increasing in the cumulative damage level.

Assaf and Shanthikumar (4) developed optimal maintenance policies for a system of N machines. Exponential lifetimes were assumed, with the same Mean Time to Failure (MTTF) for each machine. They formulated the total repair cost as the sum of a constant which reflected the overhead cost of repair and a cost of repair per machine which changed linearly with the number of failed machines. Instantaneous repairs were assumed. They also considered a second type of cost. Which incurred due to machine failures and was the same for all machines proportional to Time to Repair (TTR). They minimized the expected cost per unit time over an infinite horizon, and showed that an optimal policy is either never to repair or to repair all failed machines as soon as their number exceeds a certain threshold. They also assumed that the number of failed machines is known at every instant.

Sethi and Chand (44) focused on planning horizon results for the replacement problem. They developed three machine replace-

ment models under an improving technological environment over time, aiming at cost, erred minimization, profit maximization, and cost minimization with stochastic failures, respectively.

Oakford, Lohmann, and Salazar (39) considered technological improvement. Their model permitted implementation of technological improvement in a flexible manner without reformulating the dynamic program for each replacement problem.

Derman and smith (15) considered a system which should operate for T units of time, where T was a random variable with a known distribution function F . It was assumed that , when a vital component failed, it had to be replaced with a new component. For each component there were n possible types of replacements. The objective was to choose the type that minimized the expected total cost. of providing an operative component for the entire life of the system. They generalized the results of earlier work, where lifetimes were assumed to be exponentially distributed, enabling them to treat components with increasing failure rates.

Bryant and Murphy (13) considered systems subject to both repairable and non-repairable failures. They considered a system which was subject to three modes of failure. Type I failures were catastrophic ones, terminating the system's life. Type II failures were the ones whose damage was repairable . Type III failures were non-repairable and resulted from the system's aging. They also considered non-zero repair times.

Shaked and Shantikumar (45) studied systems whose components have dependent life lengths and failed components are imperfectly repaired until they are scrapped. They developed models in which more than one component can fail at the same time.

Numerous investigators developed some complex preventive maintenance models for which each item was replaced upon upon failure, and all identical items were replaced at multiples of some period T , without considering the ages of the items in question (46,11,12,38).

Berg (9) constructed an age replacement procedure for mission-critical items by adopting a Bayesian approach. His purpose was to ensure that the system is capable of completing the mission without a failure by controlling the reliability of mission-critical items. Berg defined p as the probability that the item will operate failure-free in the next period of some specified length l . In order to attain failure-free operation, he suggested that an item should be replaced when p falls below some specified value. He combined two uncertainties associated with the process, namely incomplete knowledge of the item's life distribution, (which is a function of a parameter, l) and the stochastic behavior of the failure process given l . In his model, Berg considered a replacement criterion which was based on failure risk.

Inöz and Perakis (23,41) studied reliability and replacement characteristics of Great Lakes marine diesel engines. A Colt-Pielstick PC2-400 series marine diesel engine has been used as a prototype for the modeling. The authors developed and implemented reliability based models to rationalize current winter layup replacement practices. Two systems have been considered: one for a ship equipped with one engine only and another for a two-engine ship. Incorporating the age dependent nature of system failure characteristics, a semi-Markov competing-process approach has been used in their models, where system failure behavior has been treated as a race among engine components. Howard's one-set, competing process model has been implemented and extended to two sets of competing processes (27). A recursive iteration procedure has been used in the expected cost calculation. Computer codes have been developed using the above models, and several examples have been examined. Sensitivity analyses have been performed for several parameters to see the influence of their variation on the expected costs and corresponding winter layup policies.

The models discussed above ignored the budget constraints usually faced in implementation. In the following section, a new de-

terministic approach which explicitly considers budget constraints is introduced. This approach is applicable to ship fleet maintenance and replacement. In addition, the same approach is equally applicable to maintenance and replacement of the components of a single ship.

CAPITAL RATIONING

Traditional replacement and maintenance models usually assume unlimited capital in practice, however decision makers frequently are restricted by limited maintenance and investment funds. Under capital rationing, the replacement and maintenance decisions must be determined simultaneously. Due to the interdependence of decisions, the computational difficulty increases significantly. In this section, we present an integer programming model and discuss a Lagrangian-based solution methodology.

The following assumptions characterize the decision environment.

- The service under consideration is provided by a number of components, each of which competes for a fixed budget in each period for maintenance or replacement.
- All cash flows and budgets are deterministic, i.e., they are known with certainty at the time of the analysis.
- Decision maker's objective is to minimize the total discounted cost of replacements and major maintenance actions over a finite planning horizon.
- Maintenance and replacement costs are dependent only on the components's age and time of installation. A key feature of this assumption is that we can specify future costs a priori using time-dependent "functional relationships" once the age-dependent costs of current components are known. Usually, these functional relationships reflect the decision maker's estimates of technological improvements and inflation for future components (39).

1. Budgets constraints are provisional limitations imposed for the purpose of controlling replacement and maintenance expenditures. They do not represent "hard" bounds in the sense Of an absolute limit on finance.

Let a zero-one Variable $X(c,a,i,j)$ be set to one if action a is taken on component in period j and doing nothing but routine maintenance until period j ; $X(c,a,i,j)$ is set to zero otherwise. Actions on a certain component can be replacing it with a new one as well as performing a major maintenance activity, such as an overhaul, a major repair and so on. Also let

- II = planning horizon,
 II = number of components,
 $P(c,a,i)$ = cost Of action a on component c in period i ,
 $B(i)$ = budget in period i . and
 $C(c,a,i,j,)$ = discounted cost of keeping component c in service from period i to period j after taking action a in period i .

Then, the problem can be formulated as an integer program as follows: Minimize

$$\sum_c \sum_a \sum_i \sum_j C'(c,a,i,j) X(c,a,i,j)$$

subject to the following constraints:

1. Replacement and maintenance actions must be sequenced in series over time on each component. These constraints are' to prevent any interruption of service. For each c :

$$\begin{aligned} \sum_a \sum_j X(c,a,0,j) &= 1 \\ \sum_a \sum_j X(c,a,i,j) - \sum_a \sum_j X(c,a,j,i) &= 0 \\ i &= 1, \dots, H \\ - \sum_a \sum_j X(c,a,j,H) &= -1 \end{aligned}$$

2. Expenditures should be within budgets. So, for $i = 0, \dots, H - 1$:

$$\sum_c \sum_a P(c,a,i) \sum_j X(c,a,i,j) \leq B(i)$$

3. Integrality

$$X(c,a,i,j) \in \{0,1\} \quad \forall c,a,i,j$$

Solving the above integer program would be significantly easier if the replacement and maintenance decisions of individual components were not interdependent by the capital rationing constraints (constraint set 2 above). This observation suggests a Lagrangian relaxation approach in which the capital rationing constraints are dualized up into the objective function with fixed multipliers. Let $\mu(i)$ be the multiplier associated with the budget constraint of period j . Then, the Lagrangian problem can be specified as follows:

$$\begin{aligned} L(\mu) = \min_r \sum_c \sum_a \sum_i \sum_j [C'(c,a,i,j) - \\ P(c,a,i) \mu(i)] X(c,a,i,j) - \sum_i B(i) \mu(i) \end{aligned}$$

subject to constraint sets 1 and.

Under certain conditions, multipliers can be determined SO that a solution of the Lagrangian problem generates an optimum solution to the original integer program satisfying the budget constraints 21). However it, is also likely that no such conditions are satisfied for a given problem data. In this case, the solution of the Lagrangian problem is still of interest for two reasons.

1. Given the assumption that the capital rationing constraints are imposed primarily for expenditure control purposes, and hence' they are usually not binding to the extent implied in the problem formulation, the Lagrangian problem may produce acceptable solutions.

2. The Lagrangian problem yields lower bounds (for minimization problems) on the optional objective of the original problem. Therefore, if a strict optimum is desired, they can be incorporated into branch-and-bound algorithms.

With Lagrangian relaxation, the problem is decomposed into n Separate and independent replacement-maintenance problems, each of which is that of finding a shortest path on an acyclic graph. We use a dynamic program to solve efficiently each shortest path problem. For a given $\mu \geq 0$, let

$$C(c,a,i,j) = C(c,a,i,j) - P(c,a,i)\mu(i)$$

for all c,a,i,j . Define $f(c,i)$ as the discounted cost of an optimum replacement and maintenance policy over a planning horizon i . Initialize $f(c,0) = 0$ for all c . For each c , the following recursive equations find the shortest path from period 0 to H .

$$f(c,j) = \min_a \min_i C(c,a,i,j) + f(c,i)$$

for $j = 1, \dots, H$. At each j , store the minimizing arguments:

$$A(c,j) = \arg\min_c f(c,j)$$

$$I(c,j) = \arg\min_i f(c,j)$$

The optimum solution is then given by a dynamic programming tree completely specified by A and I on the acyclic graph. The Lagrangian value, which is a lower bound on the optimum objective of the original integer program, is the sum of individual shortest paths minus a constant term.

$$L(\mu) = \sum_c f(c,H) - \sum_i B(i)\mu(i).$$

Finding the best multiplier vector so that the solution of the Lagrangian problem approximates the solution of the original integer program as close as possible is a nondifferentiable optimization problem. Basically, there are two approaches: 1) Subgradient algorithms, and 2) multiplier adjustment methods (MAMs).

Subgradient algorithms have been used on many practical problems Successfully. Given an initial multiplier vector, its basic step requires solving the Lagrangian problem to compute a subgradient direction for the multipliers. The multipliers are then changed in the computed direction. Details of subgradient algorithms including convergence properties can be found in (25). Held, Wolfe and Crowder (26). and Goffin (22). Karabakal (31) describes a subgradient algorithm for finding the best multipliers to solve the above' Larangian relaxation of the capital-rationed replacement and maintenance problem.

MAMs are heuristic algorithms for determining best multipliers exploiting the special structure of a particular application. The advantage of a MAM over a subgradient algorithm is that it. usually guarantees monotonic improvement of the bound. The disadvantages are' 1) it. depends on a specific problem structure, and 2) it. cannot guarantee bounds better than those obtained by a subgradient algorithm. Karabakal, Lohmann, and Beau (32) describe an efficient MAM for the capital-rationed replacement and maintenance problem when the constraint set rather than Set 2 is relaxed. They also discuss a specific branch-and-bound technique that uses this MAM as its bounding technique.

An Extension

We can extend the above formulation to include the decision situations in which the maintenance costs are dependent on the condition of the service as well as the age and time of installation of components. Suppose the conditions represent the productivity levels. After each periodic inspection, assume a component's productivity is classified into one of $L + 1$ conditions. It. is in condition 0 if it. is least costly to operate in condition L if it is most costly to operate. Then, in order to compute any future maintenance we need to know the condition of the service at the time of the maintenance action.

We assume that the decision maker can make deterministic estimates about the future conditions of the service given the cur-

rent time period, condition and the last maintenance action taken. Given the deterministic deterioration assumption one way of formulating the problem is to modify our basic formulation to incorporate the condition-dependency of maintenance costs. Let $X(c,a,i,j,j')$ be set to one if action a is taken on component c in period i at condition i' and doing nothing but routine maintenance until period j to end up with conditions j' . Redefine $C(c,a,i,j,j')$ accordingly. Then, we wish to minimize

$$\sum_c \sum_a \sum_i \sum_{i'} \sum_j \sum_{j'} C(c,a,i,i',j,j') X(c,a,i,i',j,j')$$

subject to the following constraints:

1. Replacement and maintenance actions must be sequenced in series over time on each component. For each c and i'

$$\begin{aligned} \sum_a \sum_j \sum_{j'} X(c,a,0,i',j,j') &= 1 \\ \sum_a \sum_j \sum_{j'} X(c,a,i,i',j,j') - \\ \sum_a \sum_j \sum_{j'} X(c,a,j,j',i,i') &= 0 \\ i &= 1, \dots, H \\ - \sum_a \sum_j \sum_{j'} X(c,a,j,j',H,i') &= -1 \end{aligned}$$

2. In each period, at most one' maintenance Or replacement action can be taken over all conditions, SO for each C and i :

$$\sum_{i'} \sum_a \sum_j \sum_{j'} x(c,a,i,i',j,j') \leq 1$$

3. Expenditures should be within budgets. So, for $i = 0, \dots, H - 1$:

$$\begin{aligned} \sum_c \sum_a \sum_{i'} P(c,a,i,i') \\ \sum_j \sum_{j'} X(c,a,i,i',j,j') \leq B(i) \end{aligned}$$

where $P(c,a,i,i')$ is the cost of action a on component c in period i at condition i' .

4. Integrality

$$X(c,a,i,i',j,j') \in \{0,1\} \quad \forall c,a,i,i',j,j'$$

The above formulation has many more variables and constraints than the basic formulation. However, the structure that allows us to develop efficient Lagrangian relaxation techniques for the basic model is still there. Again, when we relax the budget constraints, the Lagrangian problem consists Of many shortest path problems on acyclic graphs. Good multipliers can be determined using a MAM similar to that described for the basic model.

CONCLUDING REMARKS

First., various maintenance and replacement models with applications in the marine industry are discussed. Second, a new approach to solve the multi-item replacement under budget constraints is presented. As it, was mentioned above, a number of computer based decision support systems have been introduced to the marine industry. However, each of these systems focuses on on a specific aspect of the entire ship operation and maintenance. On the other hand, effective maintenance planning of a ship aims at minimizing failures, equipment downtime, spare parts inventory, maintenance costs and emergency maintenance simultaneously while satisfying regulations and meeting voyage schedules with a limited crew capability and under budget constraints.

Various onboard decision systems recommend a variety of maintenance actions consuming resources at different levels and assigning different replacement (or overhaul)

times depending on the user selected risk level. On the other hand, the ship fleet operator has to distribute limited resources among the ships efficiently so that the overall profitability of the shipping company is maximized. Hence the optimization model detailed above could be implemented to fleet replacement and maintenance as well as to replacement and maintenance of a single ship, considering different options under budget constraints.

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